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Abstract

One way of internalizing the externalities that each individual bank imposes on the rest of the financial system is to impose capital surcharges on them in line with their systemic importance. Given the complexity of the financial system and the resulting difficulties in measuring systemic importance, it is sometimes argued that higher capital surcharges should be applied to larger banks, abstracting from other factors like interconnectedness. In this paper, the authors consider different network structures of the banking system that are characterized by two different centrality measures. Their main finding is that size alone is not always a good proxy for systemic importance: it must be supplemented with detailed information on interbank exposures. A relatively small bank playing an outsized role in the interbank market might be more systemic, and thus garner a higher capital surcharge, than a less-connected bank of somewhat larger size. Alternatively, if the centrality of banks in an interbank network is positively correlated with their size, then proxies of a bank's systemic importance largely based on size are sufficient indicators.

JEL classification: G01, G21, C15, C81, E44
Bank classification: Financial system regulation and policies

Résumé

L'une des façons d'internaliser les externalités que chaque banque impose au reste du système financier consiste à soumettre les institutions bancaires à une exigence supplémentaire de fonds propres établie selon leur importance systémique. Cette importance étant difficile à mesurer à cause de la complexité du système financier, certains préconisent l'application aux grandes banques d'exigences supplémentaires plus élevées, sans tenir compte d'autres facteurs tels que le degré d'interconnexion. Les auteurs de l'étude considèrent diverses structures de réseau interbancaire se caractérisant par deux mesures différentes de la centralité. Leurs résultats révèlent que la taille n'est pas toujours en soi un bon indicateur de l'importance systémique : celui-ci gagne à être complété par un portrait détaillé des expositions interbancaires. Un établissement d'assez petite taille jouant un rôle disproportionné sur le marché interbancaire pourrait avoir une plus grande importance systémique et ainsi se voir assujetti à des exigences supplémentaires plus rigoureuses qu'une banque un peu plus grosse mais moins interconnectée. Les indicateurs de l'importance systémique essentiellement fondés sur la taille de l'institution ne sont adéquats que s'il existe une corrélation positive entre le degré de centralité des banques au sein d'un réseau interbancaire et leur taille.

Classification JEL : G01, G21, C15, C81, E44
Classification de la Banque : Réglementation et politiques relatives au système financier

1 Introduction

The Basel II capital standards proved to be inadequate during the 2008 global financial meltdown, partly because they were not designed to address systemic risk. In response, the post-crisis debate on regulatory reforms has devoted attention on how to induce individual institutions to internalize the costs associated with the negative externalities that their failure or non-viability may impose on the rest of the financial system. A key policy tool that has been put forward for this purpose is a regulatory capital surcharge based on an institution's contribution to systemic risk or systemic importance.

Different model-based measures of systemic importance have been proposed in the recent academic literature. While these measures might be appealing for their elegance and sophistication, implementing them can prove very tricky. Not only are they derived from complex and computationally intensive models, but they also often require detailed information at the system level that is not always publicly available. Therefore, individual institutions may find it difficult to self-assess their systemic importance based on these measures.

Alternatively, policy-makers have considered a simple indicator-based measurement approach that consists of calibrating capital surcharges based on readily available proxies for some key drivers of systemic importance, such as size, interconnectedness, lack of substitutability, global (cross-jurisdictional) activity and complexity.[1] However, the proposed indicators, including those for interconnectedness, tend to be highly correlated with bank size, suggesting that under this approach systemic importance will be determined mainly by size.

In this paper, we contribute to the regulatory debate by examining some conditions under which bank size can be a reliable proxy for more complex measures of systemic importance. In particular, we propose a method to assess under which conditions the structure of the interbank network and the role of its members are aligned with the effect of bank size, and under which conditions these are not.

For this purpose, we consider a simple stylized banking system displaying great heterogeneity across the size of banks, and derive systemic risk as well as the systemic importance of individual banks for different interbank network structures. We measure system risk with the system-wide or aggregate loss distribution derived using the model introduced in Gauthier, He and Souissi (2010). We then calibrate a bank's capital surcharge based on its marginal risk contribution to systemic risk using two allocation rules described in Albrecht (2003). An important distinguishing feature of these rules is the full-allocation property, which ensures that the sum of the individual risk contributions equals the total system-wide risk.

[1] For example, the proposed indicators for interconnectedness are generally based on aggregate interbank assets and liabilities, rather than actual individual bank-by-bank interbank exposures. For more details, see the Basel Committee on Banking Supervision (2011).

Our main finding is that proxies of a bank's systemic importance largely based on size are sufficient indicators if the centrality of banks in an interbank network is positively correlated with their size. However, bank size alone should not be considered a reliable proxy of systemic importance in interbank network structures where a relatively small bank plays an outsized role in the interbank market, making it more systemic than a less-connected bank of somewhat larger size.

The remainder of this paper is organized as follows. In section 2, we provide a brief review of the relevant literature. Section 3 succinctly describes the framework used to measure systemic risk as well as the allocation mechanisms applied to derive capital surcharges. We report our simulation results in section 4. Section 5 offers some concluding remarks and identifies possible areas for future work.

2 Literature Review

Contagion and spillover effects, which are not necessarily appropriately incorporated in market prices ex ante, represent the core amplification channels leading to systemic risk. In the financial literature, we find two main mechanisms through which shocks propagate from one financial institution or market to the other. The first works through direct counterparty credit exposures among individual institutions, and the second through information—imperfections or asymmetry—effects.[2]

In our analysis, systemic risk is triggered by network externalities produced through direct interbank exposures. Such externalities were extensively studied in the theoretical literature. For example, Flannery (1996) and Rochet and Tirole (1996) emphasize potential benefits from peer monitoring when banks are interconnected. Allen and Gale (2000) and Freixas, Parigi and Rochet (2000) show that an interbank market where all banks are interconnected may serve as a means for banks to mutually insure against idiosyncratic bank liquidity shocks.

In parallel to this theoretical literature, there are numerous empirical studies applying network techniques developed in mathematics to assess interbank spillover effects in national banking systems. For example, using the clearing algorithm introduced in Eisenberg and Noe (2001), Elsinger, Lehar and Summer (2006) and Aikman et al. (2009) find that those effects are low-probability, high-impact events. Furfine (2003) for the United States, and Sheldon and Maurer (1998) for Switzerland, find relatively benign effects, while Upper and Worms (2004) estimate a matrix of interbank loans for German banks and find some stronger evidence of spillover effects.[3] Nier et al. (2007) analyze the impact on systemic risk of different characteristics of the banking system, including capitalization and interbank market concentration.

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[2] De Bandt and Hartmann (2000) provide an extensive review of the literature on systemic risk, with a particular emphasis on information-based contagion.

[3] See Upper (2011) for a summary of the empirical literature on interbank spillover effects.

Our empirical analysis is also related to a separate stream of the literature that measures the systemic importance of individual institutions using standard risk-management techniques. In this literature, the systemic importance of a bank is deemed equal to its contribution to systemic risk. One strand of this literature measures systemic importance based on banks' balance-sheet data. For example, Gauthier, Lehar and Souissi (2010) use a network of Canadian financial institutions and compare alternative mechanisms for allocating the overall risk of a banking system to its member banks. They find that systemic importance is not trivially related to size and increases with interbank assets. Tarashev, Borio and Tsatsaronis (2009), for example, apply Shapley values to measure the systemic importance of banks, and find that it increases with bank size. They do not, however, consider the risk that banks impose on each other through interbank linkages. Drehmann and Tarashev (2011) propose an approach to doing so, but their results are strongly dependent on their assumptions on how interbank assets should be reallocated in any given subset of banks analyzed in calculating the Shapley value, and on their unconventional definition of system-wide losses, which are assumed to equal only losses incurred by non-bank creditors to banks, rather than the more standard approach of total bank losses. Another stream relies on market data. Acharya et al. (2010) measure the contribution to systemic risk of individual institutions as their systemic expected shortfall (SES), and demonstrate empirically the ability of SES to predict emerging risks during the financial crisis. Zhou (2010) measures systemic importance under a multivariate extreme-value-theory framework and finds that size should not be considered as a proxy for systemic importance.

We base our analysis on stylized bank balance-sheet data, since spillover externalities are, by definition, not explicitly taken into account by markets, which questions the relevance of market data to assess their impact. Conditional on the availability of reliable data, the balance-sheet approach may be more appropriate than market data to assess the extent of externalities in the financial system.

3 Measurement of Systemic Risk and Systemic Importance

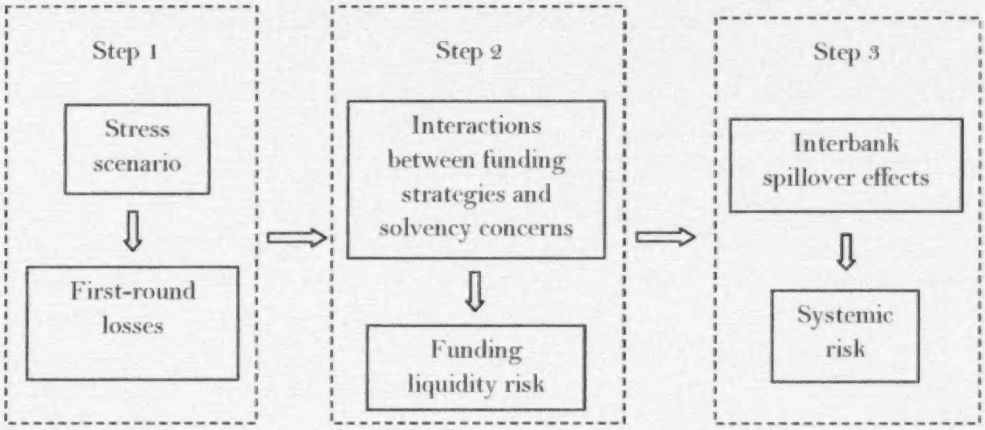
This section describes our analytic framework. The first subsection introduces a model for systemic risk that allows for different sources of risk in a stylized banking system. The second subsection presents the two rules used to derive the contribution of individual institutions to systemic risk and corresponding capital surcharges. The third subsection describes the network structures and centrality measures considered in our simulations.

3.1 A framework for measuring systemic risk

We follow Gauthier, Lehar and Souissi (2010) and use an amount of losses that exceeds a certain threshold in the tail of aggregate bank losses—which include losses incurred by both the banks'

equity and debt holders—as the measure of systemic risk.[4] These losses are generated using the 2-period framework introduced in Gauthier, He and Souissi (2010). This framework is derived from a class of macro stress-testing models used by central banks and international financial institutions to identify vulnerabilities in the financial sectors of the economy.[5] It explicitly characterizes balance sheets for banks, and allows for first-round losses reflecting risks associated with banks' assets (such as credit and market risks), funding liquidity risk and network interactions. The basic structure of this framework and the mapping from shocks to systemic risk are illustrated in Figure 1.

Figure 1: Basic Structure of the Framework for Systemic Risk



In the first step, banks are subject to common adverse macroeconomic shocks that engender first-round asset losses that are expected to occur over a forward 1-year horizon. Specifically, the model maps slowdowns in economic activity to increases in the probability of default of the banks' portfolio of assets. Given data on bank exposures and an assumed loss-given-default rate, this in turn generates bank losses over the 1-year horizon.

In the second step, bank-funding liquidity risk is introduced, consistent with recent advances in the theoretical banking literature and the experience of the recent financial crisis.[6] Specifically, in extreme circumstances, where a bank's lenders have concerns about the bank's future

[4] There is no clear consensus on how systemic risk should be measured in the literature. For example, Drehmann and Tarashev (2011) use a more restrictive measure of systemic risk, which excludes losses incurred by equity holders. They argue that equity is fully loss absorbing, and that equity losses do not have systemic implications as long as banks' capital remains positive. In our analysis, we include equity losses in the measurement of systemic risk for at least two reasons. First, current capital requirements are designed to cover only unexpected losses associated with banks' intrinsic or idiosyncratic riskiness. As such, equity is not necessarily fully absorbing when adverse externalities that a bank is subject to are taken into account. Second, from a macroprudential perspective, these losses can have systemic repercussions, since they could adversely impact the ability of the financial system to generate credit in the economy, which may lead to disruptions in financial intermediation.

[5] See Foglia (2009) for a literature survey of macro stress-testing models.

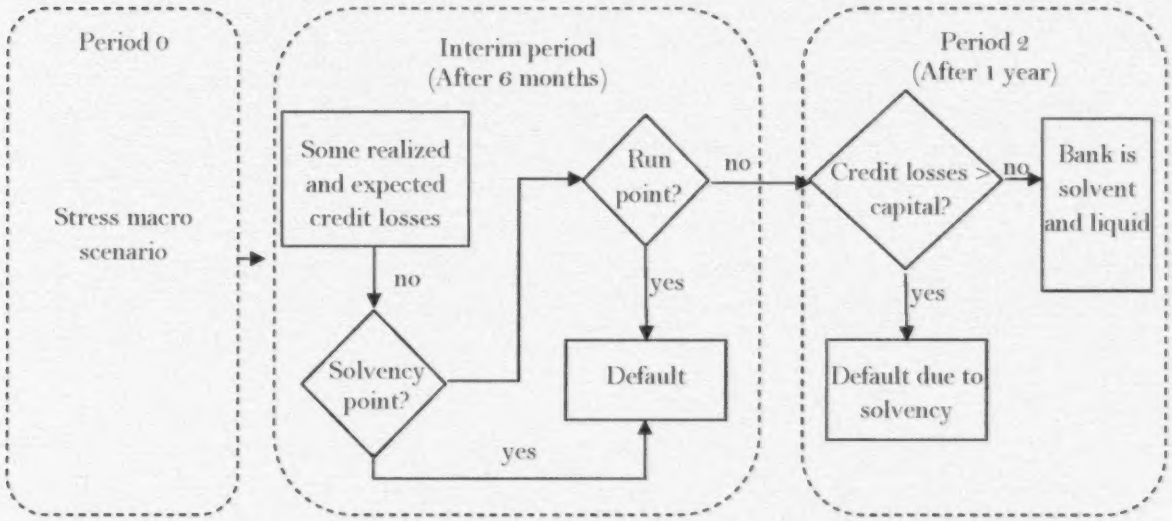
[6] The modelling of liquidity funding risk follows the game theory model described in Morris and Shin (2009).

solvency, they may refrain from rolling over their short-term claims. In the second step, potential runs by short-term lenders become more likely if the bank has small amounts of liquid assets and/or high reliance on short-term wholesale funding. Banks that are vulnerable to rollover risk can be forced to sell their illiquid assets at a large discount, which would generate additional losses.

In concrete terms, the 1-year horizon is divided into three periods: period 0, at the beginning of the year, where only the distribution of first-round losses is known; period 1, after six months, at which time some loan book losses are realized, potentially leading to interim insolvency, illiquidity (of solvent banks) or neither event; and period 2, the end of the year, at which time any additional and final total credit losses are observed and liquid banks become insolvent or remain solvent.

It is in the interim period where funding risk materializes. In the interim period, there could be a coordination problem among a bank's short-term debt holders. A key variable in their decision regarding whether to roll over their claims on a bank is their beliefs about the proportion of other short-term creditors expected to roll over. If short-term debt holders do not roll over their debt, banks will sell their liquid assets and a share of their illiquid assets, the latter at a loss. This potentially generates the bank's default in its own right, depending on the amount of losses incurred via the illiquid-asset fire sale. Figure 2 provides an overview of step 2, where we assess the risk of bank default generated by funding risk.

Figure 2: Approach to Assessing Liquidity and Solvency Risks



Step 3 (in Figure 1) of the process generates systemic risk through interbank spillover effects, using the clearing algorithm introduced in Eisenberg and Noe (2001). A defaulting or non-viable bank will not be able to fulfill its obligations in the interbank market, imposing counterparty credit losses on other banks in the system, and potentially leading to their default.[7] These interbank or knock-on losses are realized only after the banks' individual losses occur, and are a function of the banks' direct exposures to each other.

3.2 Measurement of systemic importance and capital surcharge

In order to understand the importance of a bank's interconnectedness for its contribution to systemic risk, a set of loss distributions, with and without network effects, are generated with the macro stress-testing model described above. Define L^n, L, l_i, and l_i^n as the realized loss of the whole financial system with network externalities, the realized loss of the whole financial system without network externalities, and the losses of individual institutions indexed by i, with and without network externalities, respectively. In the remainder, we index variables with n to indicate that network effects are in place.

Consider $R(L)$ as the aggregate capital required to cover a given distribution of aggregate non-network losses L. We use the expected shortfall (or $CVaR$) as our *aggregate* risk measures:

$$R(L) := CVaR_\alpha(L) = E[L \mid L \geq VaR_\alpha(L)],$$

where $VaR_\alpha(L)$ is the value-at-risk of L at confidence level α.[8] The same measure of aggregate capital can be calculated when the network is in place, $R(L^n)$.

Let also $\rho(l_i)$ be the idiosyncratic (or stand-alone) risk capital required from institution i when the interconnections between institutions are ignored, and $\rho(l_i^n)$ be the total risk of institution i; i.e., including its contribution to the risk of the whole financial system through network interconnections.

We next follow Albrecht (2003) and propose two rules for allocating risk capital to individual institutions. The two capital-allocation rules fulfill the following basic full-allocation requirement[9]:

$$\sum_{i=1}^{n} \rho(l_i^n) = R(L^n). \qquad (1)$$

---

[7] A non-viable bank is one with a serious capital shortfall. As such, it may have a positive level of capital but is assumed to be incapable of, or precluded from, paying interbank liabilities due possibly to resolution or bankruptcy procedures.

[8] Expected shortfall tells us how bad things can get conditional on something very bad happening. It has the advantage over the value-at-risk of being a consistent measure of risk (Denault 2001).

[9] See Albrecht (2003) for an introduction to more stringent requirements.

The beta principle

We first use the beta principle defined as:

$$\rho(l_i^n) := E(l_i^n) + \frac{cov(l_i^n, L^n)}{var(L^n)}[R(L^n) - E(L^n)]$$

$$= E(l_i^n) + \beta_i[R(L^n) - E(L^n)],$$

where the total contribution of bank i is defined as its contribution to system-wide expected losses, $E(l_i^n)$, plus its contribution to system-wide unexpected losses, $[R(L^n) - E(L^n)]$, the latter being measured by its contribution to the variance of losses in the system, β_i.

The conditional-expectation principle

Finally, the fact that $R(L) = E[L|L = R(L)] = \sum_{i=1}^{n} E[l_i \ | L = R(L)]$ suggests the following definition of individual risk capital[10]:

$$\rho(l_i^n) = E[l_i^n | L^n = R(L^n)].$$

The contribution of a bank is the expected loss of that bank when the whole system is at its expected shortfall. This principle is the same as the SES method proposed by Acharya et al. (2010) and clearly fulfills our basic full-allocation requirement (1).

It is also easy to show that the beta principle fulfills (1), since $\sum_{i=1}^{n} E(l_i^n) = E(L^n)$, and $\sum_{i=1}^{n} \beta_i = 1$. There are alternative allocation methods, including the CoVar, incremental VaR and Shapley values. All three do not fulfill our basic full capital-allocation requirement. Moreover, the incremental VaR and Shapley values require measuring risk in different subsets of banks, and the results of applying these methods depend on the assumptions made regarding the reallocation of interbank assets of the banks not included in any given subset.[11]

The capital surcharge imposed on bank i, (KS_i), to reflect the spillover effects through the network, is simply defined as the difference between the total risk of the bank and its stand-alone risk:

$$KS_i := \rho(l_i^n) - \rho(l_i).$$

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[10] The same definition applies when the network is not in place; i.e., $\rho(l_i) = E[l_i \ | L = R(L)]$.

[11] See Gauthier, Lehar and Souissi (2010) for an application of all these methods.

The capital surcharge can also be decomposed in terms of expected and unexpected losses with and without network effects:

$$KS_i = \rho(l_i^n) - \rho(l_i) = E(l_i^n) \quad + UL_i^n - \left[E(l_i) \quad + UL_i\right],$$

where UL_i^n and UL_i denote the unexpected loss of bank i with and without the consideration of the network, respectively. Hence, the capital surcharge includes a correction for both the change in expected loss and the change in unexpected loss due to the network.

3.3 Network structures and centrality measures

We consider a fictitious banking system composed of four banks (or brackets of banks of similar size). The banking system is very heterogeneous in terms of bank size: in size, the four banks are 300, 1,000, 2,000 and 3,000 billion U.S. dollars, respectively. This is representative of the observed size dispersion for the larger set of international active banks.[12] All banks are assigned the same level of initial capital and short-term funding, but they differ in terms of the intrinsic riskiness of their assets and their degree of interconnectedness. The intrinsic riskiness is randomly different across the banks and uncorrelated with a bank's size. These differences in bank characteristics allow us to separate a bank's capital requirement due to its intrinsic or idiosyncratic riskiness from a capital requirement to cover for the network externality it imposes on the rest of the banking system.

We run simulations for different network structures and size. We first study simple network structures where the only interconnections are between each bank and a "central" bank. That is, the banks not in the centre are not interconnected to each other and are net borrowers from the "central" bank. We consider the cases where the "central" bank is either the largest or the smallest bank (structures 1 and 2 hereafter). These two "central" bank structures are illustrated in Figure 3, where banks' sizes are represented by the size of the corresponding circles. The interbank exposures (IBEs) are set at 10 per cent, 20 per cent (as in Nier et al. 2007) or 30 per cent of the "central" bank's total assets. In both structures, the central bank lends to the three others proportional to their size. Therefore, the size of the interbank flows or connections increases with the aggregate interbank exposures, the central bank's size and the size of the borrower.

We also study two more complex network structures where all banks are connected to each other via interbank lending/borrowing (structures 3 and 4 hereafter). In structure 3, each bank's total interbank assets are set at 10 per cent, 20 per cent or 30 per cent of its total assets, and bilateral interbank assets are distributed proportional to the banks' size. In structure 4, each bank's total interbank assets are set at 10 per cent, 20 per cent or 30 per cent of the smallest bank's total

[12] As an example, one of the largest banks worldwide, RBS, held US$3.6 trillion at the end of 2007, and 300 billion corresponds roughly to the size of Canada's smallest bank among the big five.

assets, and bilateral exposures are uniformly distributed.[13] Table 1 illustrates the interbank exposures in each of the four structures in the case where total IBEs are set at 10 per cent.

Figure 3: Simple Network Structures (1 and 2)

Figure 3(1): Biggest bank as the centre

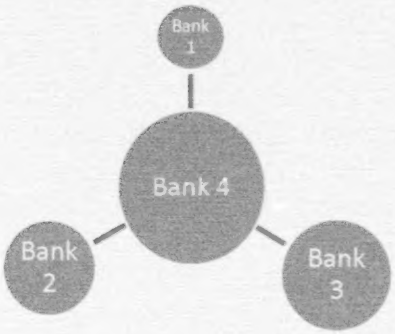
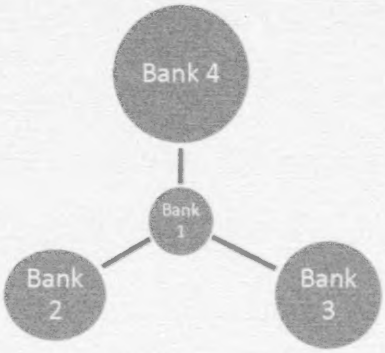


Figure 3(2): Smallest bank as the centre



We use two measures of centrality. The first, which is in line with the Basel Committee on Banking Supervision's proposed measure of interconnectedness, is the net interbank asset (NIA) position of the banks.[14] This measure relies on aggregate information on interbank exposures, rather than bilateral exposures. The second centrality measure, called *eigenvector centrality*, depends not only on the number of one bank's interconnections but also on the centrality of its counterparties. That is, the more central the neighbours of a bank are, the more central is that bank itself (Bonacich 1987).[15]

[13] As a robustness check, we consider below random matrices of interbank exposures that match the row and column sums of structure 3.

[14] In the network terminology, this corresponds to the difference between the out-degree centrality (assets) and the in-degree centrality (liabilities) of each bank.

[15] More precisely, the centrality of bank i, e_i, is proportional to the sum of its interconnections weighted by the centrality of the corresponding neighbours:

$$e_i = \frac{1}{\lambda}\sum_{j=1}^{n} A_{ij}e_j,$$

where A is the interbank exposures matrix, λ its largest eigenvalue and $e \equiv (e_1, e_2, \ldots, e_n)^T$ the corresponding principal eigenvector.

Table 1: Bilateral interbank exposures in the four different network structures for total IBEs=10 per cent (in billions). For each structure, numbers in columns represent interbank assets. In structures 1 and 2, the central bank lends to other banks proportional to their size. In structure 3, all banks lend to each other proportional to their size. In structure 4, all banks are uniformly exposed to each other.

Structure 1

Bank1	Bank2	Bank3	Bank4
0	0	0	27
0	0	0	91
0	0	0	182
0	0	0	0

Structure 2

Bank1	Bank2	Bank3	Bank4
0	0	0	0
5	0	0	0
10	0	0	0
15	0	0	0

Structure 3

0	6	14	27
5	0	47	91
10	38	0	182
15	57	140	0

Structure 4

0	10	10	10
10	0	10	10
10	10	0	10
10	10	10	0

According to both measures, bank 4 (bank 1) has the largest centrality measure in structures 1 and 3 (structure 2), and there is no "central" bank in structure 4.[16] Measuring centrality is more challenging in complete networks: while the rank of banks in terms of centrality is the same under both measures for the simple structures (1, 2 and 4), it varies substantially for the more complex structure 3 (see Table 2). Whereas bank 4 is the more central bank according to the first measure, it is the least central bank following the eigenvector centrality method.

Table 2: Centrality measures in the four different network structures for IBEs=10 per cent. The first measure of centrality shown is the net interbank asset position and the second is the eigenvector centrality measure.

	Structure 1	Structure 2	Structure 3	Structure 4
Bank 1	(-27, -0.13)	(30, 0)	(-17, -0.14)	(0, -0.50)
Bank 2	(-91, -0.44)	(-5, -0.26)	(-42, -0.43)	(0, -0.50)
Bank 3	(-182, -0.88)	(-10, -0.53)	(-29, -0.65)	(0, -0.50)
Bank 4	(300, 0)	(-15, -0.80)	(88, -0.60)	(0, -0.50)

[16] All banks have zero NIA centrality in structure 4; nevertheless, the network will still have effects, since the interbank payments are derived without netting banks' interbank positions.

4 Results

In our simple settings, we can assess whether size or centrality has more impact on systemic importance. Table 3 shows the correlations between capital surcharges (KS) and size, KS and centrality, and size and centrality (for both NIA and eigenvector centrality measures and under both allocation methods).[17] Let us start with the two simplest network structures, 1 and 2. The correlations between KS and centrality are positive and strongly significant in both structures, and under both allocation methods. The correlation between size and KS is positive in structure 1, where centrality is positively correlated to size, and negative in structure 2, irrespective of the capital-allocation method.[18] More central banks receive higher capital surcharges whether they are small or large.[19] Centrality is therefore a better proxy than size for systemic importance in those simple networks.

For structure 4, in which no bank is central, KS and size are significantly negatively correlated. The fact that the smallest banks lend proportionally more than the big ones in that structure (relative to their balance-sheet size) seems to drive this result. Smaller banks are relatively more vulnerable to their counterparties being in trouble in the interbank system, and are consequently required to hold more capital to mitigate this network risk. When all banks are equally central and centrality has no role to play in the determination of capital surcharges, small banks could still need to hold more capital than larger ones, since they are proportionally more dependent (or exposed) than larger banks to the network. Thus, under more realistic conditions, where banks increasingly become involved in interbank or wholesale markets as they mature and grow, and in turn more exposed to the network, this result is not likely to hold. In fact, network structures such as 1 or 3 are more likely.

Within the more complex structure 3, where the network is complete, the analysis is not as straightforward. The correlation between KS and size is not significant under both allocation methods, but the degree of significance of the correlation between KS and centrality varies with the measure of centrality. As a robustness check, we generate 1,000 random matrices of interbank exposures that match the row and column sums of that structure. This allows for the analysis of a large spectrum of networks where exposures vary from strongly concentrated to evenly distributed.

Table 3 shows that the correlation between KS and centrality is strongly positive under the NIA centrality measure, but not significant under the eigenvector centrality measure. This emphasizes the difficulty of measuring centrality in complete networks. Table 3 also shows that the correlation between KS and size is significant in more than 80 per cent of the simulated

[17] The model is run for 1,000 loss scenarios and 12 different network structures, which allows for the calculation of significance levels.

[18] In particular, under the conditional-expectation principle, only bank 4 (1) has a surcharge imposed on it in structure 1 (2).

[19] Gauthier, Lehar and Souissi (2010) find the same correlation in a calibrated network of six Canadian banks.

networks, but varies strongly with the distribution of bilateral exposures. It can be as low as 0.3 and as high as 0.75. Therefore, size alone is not always a good proxy for systemic importance within complete networks. Given that different centrality measures convey different information, size must be supplemented with information on bilateral exposures.[20]

Table 3: Correlations between KS and size, and KS and centrality for different network structures and capital-allocation methods. The last two rows report the correlation between size and centrality for two centrality measures and different network structures. Column 6 provides average correlations for the 1,000 random structures that match the row and column sums of structure 3. Minimum and maximum correlations are shown in parentheses.

	Structure 1	Structure 2	Structure 3	Structure 4	Random Structure 3
Beta principle					
Corr(KS,Size)	0.80***	-0.63***	0.35	-0.35*	0.58[1] (0.29, 0.75)
Corr(KS, NIA centrality)	0.87***	0.95***	0.69***	0	0.83[2] (0.63, 0.93)
Corr(KS, eigen centrality)	0.66***	0.69***	0.09	0	0.02[3] (-0.39, 0.38)
Conditional-expectation principle					
Corr(KS,Size)	0.67***	-0.57***	0.32	-0.13	0.42[4] (0.13, 0.63)
Corr(KS, NIA centrality)	0.70***	0.82***	0.27	0	0.38[5] (0.21, 0.71)
Corr(KS, eigen centrality)	0.51**	0.62***	-0.24	0	0.01[6] (-0.47, 0.47)
Correlation between size and centrality					
Corr(Size, NIA centrality)	0.62**	-0.76***	0.73***	0	0.73***
Corr(Size, eigen centrality)	0.15	-0.99***	-0.81***	0	0.01[7] (-0.9, 0.9)

*, ** and *** mean significant at the 10%, 5% and 1% levels, respectively.

1. 81% of the cases significant at the 5% level and all positive.
2. 100% of the cases significant at the 1% level and all positive.
3. 100% of the cases non-significant.
4. 70% of the cases significant at the 5% level and all positive.
5. 25% of the cases significant at the 5% level and all positive.
6. 26% of the cases significant at the 5% level, among which 10% are positive and 16% negative.
7. 99% of the cases significant at the 1% level, among which 50% are positive and 49% negative.

[20] To test for the robustness of our results, we invert the directions of the links between banks (we simply transpose the matrices of interbank exposures). Banks that had been net lenders to their counterparts in the interbank network now become net borrowers, and vice versa. For example, bank 4 is borrowing in the interbank market (instead of lending) in structure 1, and the first three banks now have net interbank assets in structure 3 instead of net interbank liabilities (recall Table 2). The results are qualitatively the same and are available upon request.

5 Conclusion and Future Work

Size should not automatically be considered as the best proxy for systemic importance. In the simple settings studied in this paper, we find evidence that systemic importance can be driven more by how a bank is interconnected with others than by its size. A relatively smaller bank playing a big role in funding markets (or an outsized role in the interbank market relative to its total asset size) might garner a relatively higher capital surcharge than a less-connected bank of the same or somewhat larger size. However, when bank size is correlated with centrality, the capital surcharge is, in reality, positively correlated to size in any network structure. This implies that, if, in normal circumstances, the centrality of a bank in an interbank network is in fact positively correlated with bank size, then proxies of a bank's systemic importance largely based on size are sufficient indicators. Thus, verification of the validity of the Basel Committee on Banking Supervision's proposed systemic importance indicators would hinge on empirically assessing the actual underlying relationship between a bank's (total asset) size and its true underlying degree of interconnectedness. This would require detailed interbank network exposure data that are currently not readily available in most jurisdictions.

Our analysis has focused on contagion stemming from direct interbank exposures. However, other channels of contagion that are not modelled here could modify our findings. For example, we do not model the potential contagion that can occur via the propagation of bank runs across a set of banks driven by short-term uncertainty among bank creditors. Secondly, we do not model the negative impact on credit intermediation and the real economy that would result from the collapse of a large bank. The slowdown led by a contraction in intermediation or a contraction in real economic activity might, in turn, have a negative impact on bank assets and generate further losses in the banking sector. Measuring these second-round impacts would likely bias the measure of banks' systemic importance toward those that are larger and more important creditors to the real (rather than the banking) sector. These two missing, more realistic aspects of our modelling framework are left for future work.

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